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Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems—A review

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A B S T R A C T

In this paper, an attempt has been made to review the applications of artificial neural networks (ANN) for energy and exergy analysis of refrigeration, air conditioning and heat pump (RACHP) systems. The studies reported are categorized into eight groups as follows: (i) vapour compression systems (ii) RACHP systems components, (iii) vapour absorption systems, (iv) prediction of refrigerant properties (v) control of RACHP systems, (vi) phase change characteristics of refrigerants, (vii) heat ventilation air conditioning (HVAC) systems and (viii) other special purpose heating and cooling applications. More than 90 published articles in this area are reviewed. Additionally, the limitations with ANN models are highlighted. This paper concludes that ANN can be successfully applied in the field of RACHP systems with acceptable accuracy.

Contents

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1. Introduction

The performance of refrigeration, air conditioning and heat pump (RACHP) systems are analyzed in terms of first law (energy analysis) and second law (exergy analysis) of thermodynamics using conventional approaches (analytical and experimental methods). The conventional analytical approach involves more complicated analytical equations and theoretical assumptions, whereas experimental studies are more expensive and time consuming. During last two decades, the use of artificial intelligence systems in refrigeration and air conditioning field is increasing gradually to solve the complicated problems. Artificial intelligence systems include areas such as expert systems, ANN, genetic algorithms, fuzzy logic and various hybrid systems, which combine two or more techniques [1,2]. The main advantages of ANN compared to other expert systems are its speed, simplicity and ability of modeling a multivariable problem to solve complex relationships between the variables and can extract the non linear relationships by means of training data [1,2]. ANN overcomes the limitations of conventional approaches by extracting the required information using training data, which has not required any specific analytical equations. ANN model can predict the desired output of the system using limited training data.

Many review studies were reported with applications of ANN in the field of drying processes [3], for forecasting [4], for atmospheric sciences [5], for sizing of solar photovoltaic systems [6] and for modeling of energy systems [7–9]. Ding [10] summarized the various simulation techniques for modeling and performance prediction of vapour compression refrigeration systems. Following the previous reviews cited, it is understood that there is no specific review reported on applications of ANN for RACHP systems. The present review set out more broadly about up to date study covering the applications of ANN in energy and exergy analysis of RACHP systems, prediction of refrigerant properties and control of RACHP systems. Moreover, the limitations with ANN models are highlighted.

2. Artificial neural network architectures – an overview

Artificial neural networks (ANN) try to mirror the brain functions in a computerized way by restoring the learning mechanism as the basis of human behavior. ANN can operate like a black box model, which requires no detailed information about the system or equipment. ANN can learn the relationship between input and output based on the training data. The structure of artificial neuron is illustrated in Fig. 1. ANN is a nonlinear informational processing device, which is built from interconnected elementary processing devices called neurons. Each input is multiplied by a connection weight. The product and biases are summed and transformed through a transfer function (consists of algebraic equations) to generate a final output. The process of combining the signals and generating the output of each connection is represented as weight. Most commonly used network architectures in the field of RACHP are (i) multi-layer feed forward, (ii) radial biased function network, (iii) generalized regression neural networks and (iv) adaptive

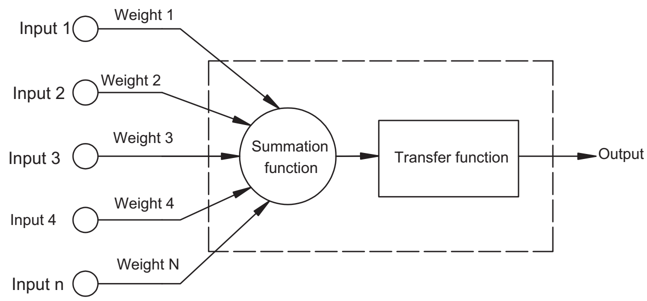

Fig. 1. Structure of an artificial neuron [1,2].

neuro fuzzy systems. An overview of various ANN architectures is discussed in this section.

2.1. Multi layer feed forward networks (MLFFN)

An illustration of MLFFN is given in Fig. 2, which has an input layer, followed by one or more hidden layers and an output layer [1,2]. Multiple layers of neurons with nonlinear transfer functions allow the network to learn linear and nonlinear relationships between input and output vectors. Back propagation learning algorithm is widely used to train the MLFFN. The network is trained with selected number of neurons in the hidden layer, momentum factor, learning rate and transfer function. MLFFN is more suitable for performance prediction of RACHP systems. The number of neurons in input layer is equal to the number of parameters that affects the performance of RACHP systems and the number of neurons in output layer corresponds to the number of parameters to be predicted.

2.2. Radial biased function network (RBFN)

The construction of RBFN involves three layers such as input layer, hidden layer followed by an output layer [1,2]. The interconnections between input layer and hidden layer form hypothetical connections and between the hidden layer and output layer form weighted connections. The input layer is made up of source nodes; the second layer is a hidden layer of high enough dimensions followed by an output layer, which gives response of the network. The Gaussian transfer function is used to operate the weighted inputs to produce neuron output. The activation function used in hidden layer is radial base function. The linear transfer function is used in output layer. RBFN has faster convergence, smaller extrapolation errors and has higher reliability compared to MLFFN. The structure of RBFN is depicted in Fig. 3.

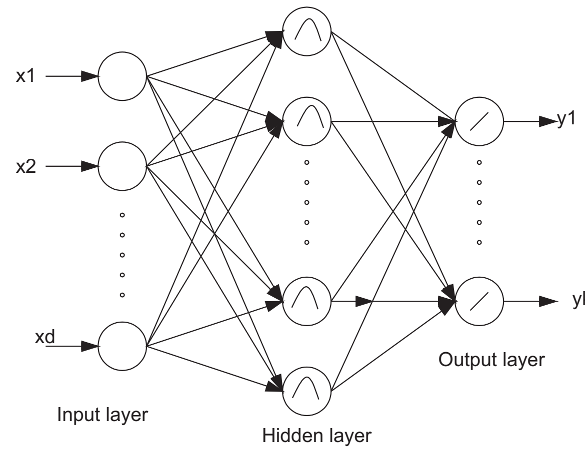

Fig. 3. Structure of RBFN [1,2].

2.3. Generalized regression neural network (GRNN)

GRNN is a four-layer feed forward neural network based on the non-linear regression theory consisting of input layer, pattern layer, summation layer and output layer [1,2]. The configuration of GRNN is illustrated in Fig. 4. GRNN is a memory-based feed forward networks based on the estimation of probability density functions. There are no training parameters such as learning rate and momentum factor, as there are in back propagation networks, but there is a smoothing factor applied after the network is trained. The summation layer has two different types of processing units (the summation units and a single division unit). Each of the GRNN output units is connected only to its corresponding summation unit and to the division unit. The summation and output layers together basically perform a normalization of the output vector. Radial base and linear transfer functions are used in hidden layer and output layer, respectively.

2.4. Adaptive neuro fuzzy interface systems (ANFIS)

ANFIS is a MLFFN consisting of nodes and directional links, which combines the learning capabilities of a neural network and reasoning capabilities of fuzzy logic [11]. The structure of ANFIS is depicted in Fig. 5. This hybrid structure of the network (ANFIS) can extend the prediction capabilities beyond ANN and fuzzy logic techniques when they are used alone. ANFIS architecture consists of fiver layers. The first layer in the network is called fuzzy layer. The adjustable nodes in this layer are represented by square nodes and

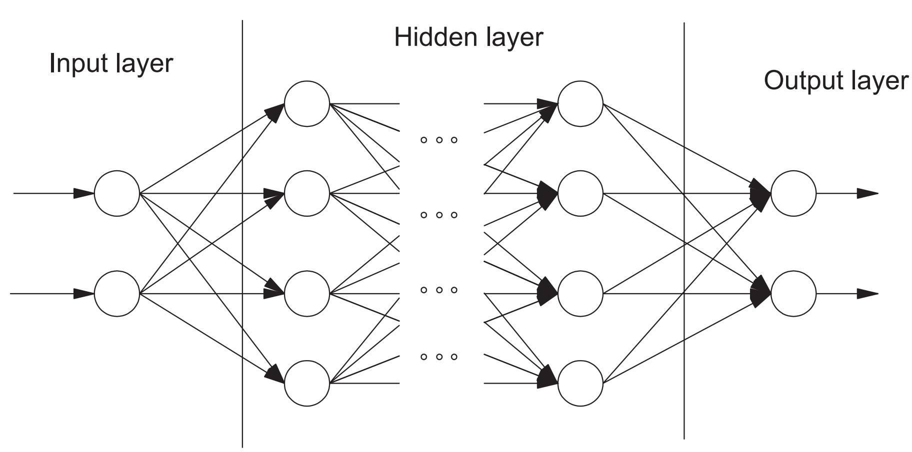

Fig. 2. Structure of MLFFN [1,2].

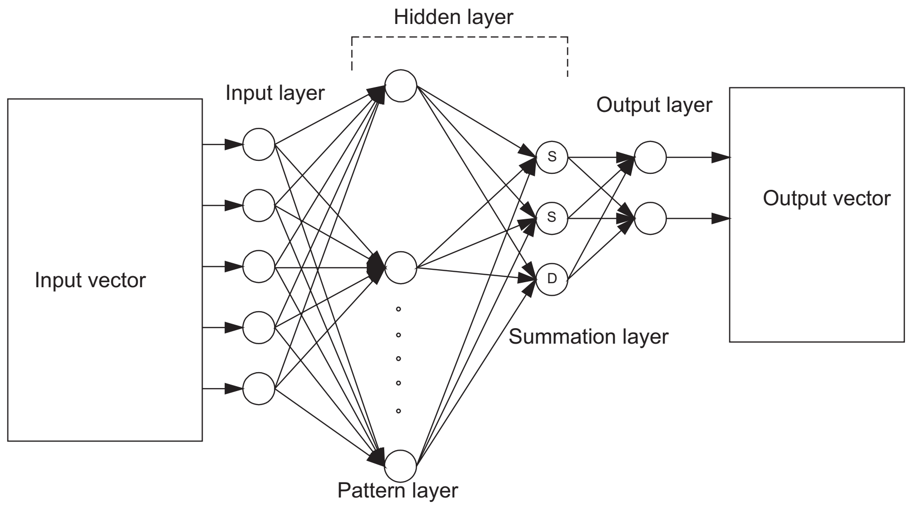

Fig. 4. Structure of GRNN [1,2].

marked by A_1, A_2, B_1 and B_2 with x and y outputs. The second layer is called product layer and every node in this layer is a fixed node marked by a circle node and labeled by M. The outputs w_1 and w_2 are the weight functions of the next layer. The third layer is a normalized layer and every node in this layer is a fixed node, marked by a circle node and labeled by N. The nodes normalize the firing strength by calculating the ratio of firing strength for this node to the sum of all the firing strengths. The fourth layer is the de-fuzzy layer having adaptive nodes and marked by square nodes. The fifth layer computes the overall system output as the summation of all incoming signals.

2.5. Applications of ANN in the field of RACHP systems

Some of the major applications of ANN in refrigeration and air conditioning field are listed below.

Forecasting
- Air conditioning load.
- Performance of the RACHP systems.
- Environmental impacts of RACHP systems.

Refrigerant mixture properties
- Thermodynamic and thermo-physical properties of refrigerant mixtures.
- Properties of refrigerant and absorbent pairs.
- Phase change characteristics.

Control systems
- Controlling of RACHP systems.

Optimization and decision making
- Optimization of energy usage in RACHP systems.

The applications of ANN for above field are discussed in Section 4.

3. Modeling with artificial neural networks

ANN modeling is carried out in four steps as follows: (i) extract the results from experiments or theoretical calculations (ii) train the network using experimentally or theoretically predicted values (iii) testing of network with data, which are not used for training, (iv) identify the best network architecture based on statistical performance values [1,2].

3.1. Selection of network parameters

The parameters such as number of neurons in input, hidden and output layers, network architecture, transfer function, learning algorithm, momentum factor and learning rate are selected for develop ANN model. The number of input neurons in input layer is equal to number of parameters that affects the performance of RACHAP systems. The input layer distributes the values to each neuron in hidden layer. A layer of processing neurons that is between the input and output layer is called hidden layer. The number of hidden layers and optimum number of hidden neurons may vary

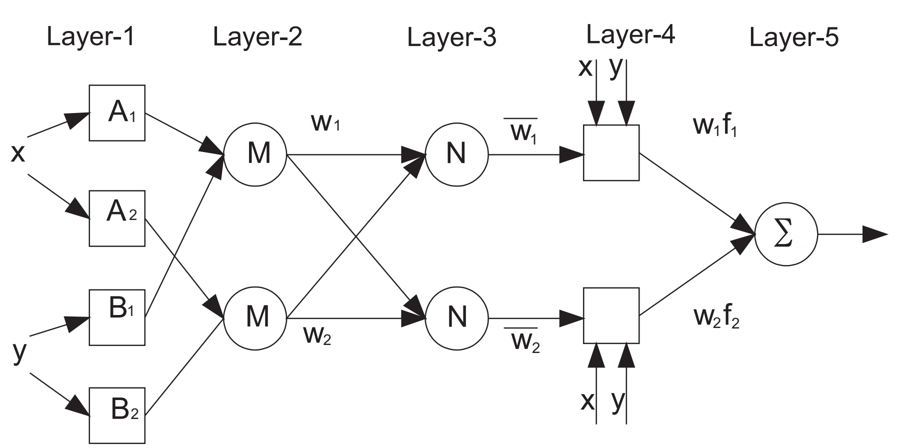

Fig. 5. Structure of ANFIS [11].

depending on the accuracy required. The number of neurons in the hidden layer, number of hidden layers, momentum factor and learning rate values are optimized by trial and error method to attain results with good accuracy. The number of neurons in output layer is equal to number of parameters selected for predicting the performance of RACHP systems.

Transfer function consisting of algebraic equation, which is either linear or non linear form. Most commonly used transfer functions are log-sigmoid and tangent sigmoid. The log-sigmoid transfer function has been chosen for hidden layer and output layer, if all the values in input and output layer are positive. The inputs and outputs are normalized in 0–1 range. log-sigmoid transfer is given by

$$f(z) = \frac{1}{(1+e^{-z})}, \tag{1}$$

If negative value exists in input or output layer, tangent sigmoid transfer function has been preferred. Tangent sigmoid transfer function is given by

$$f(z) = \frac{(1-\mathrm{e}^{-2z})}{(1+\mathrm{e}^{-2z})} \tag{2}$$

The inputs and outputs are normalized in the range between −1 and 1. Here Z is a function of $z = f(\sum w_i x_i)$, i is the index on inputs to neuron, x_i is the input to neuron, w_i is the weighted factor attached to input, z is the weighted input.

Back propagation algorithm (BPA) is most widely used in ANN, which has different variants. BPA optimizes the weight connection by allowing the error to spread from output layers towards the lower layers (hidden layer and input layer). The network output is compared with desired output and errors were computed. These errors were then back propagated for adjusting the weight such that the errors decrease with each iteration and ANN model approximated the desired output. The network is trained to achieve the error goal of 10^{-6}.

3.2. Training of network

ANN is trained with set of known input–output data and suitable learning method to perform a function by adjusting the values of weight coefficient between processing neurons. The training process continues until the network output matches with desired output. Changing the weights and biases reduces the error between the network output and desired output. The training process is terminated automatically when the error falls below a determined value or the maximum epochs is exceeded. Basic steps for using ANN are described as follows, which is also depicted in the flow chart (Fig. 6):

(i) Identify the parameters which influence the performance of the RACHP system (neurons in the input layer) and the performance values of the system selected prediction (neurons in the output layer). Eliminate constant parameters.
(ii) For the exergy analysis of the RACHP systems, ambient temperature should be selected.
(iii) The input–output data extracted from experiments were divided two sets (training input-output data and testing output data). About 70% of the input–output data selected randomly are assigned as training set data and remaining data can be used for testing the network.
(iv) Develop an ANN model and define the inputs and outputs.
(v) Normalization of input and outputs either in the range between 0 and 1 or between −1 and 1 depending on the type of data and transfer function used.
(vi) Train the network with normalized input and output values using MATLAB-neural network tool box.
(vii) Extract the results using the network for testing input–output data, which are not used in training of network.
(viii) Calculate the statistical performance values such as absolute fraction of variance, correlation coefficient, coefficient of variance and root mean square values by changing the number of hidden layers, number of hidden neurons, transfer function, etc.
(ix) Select the best network architecture based on statistical performance values (having higher correlation coefficient and absolute fraction of variance with lower values of root mean square error and coefficient of variance).

3.3. Testing of network

The criteria used for measuring the performance of the network are correlation coefficient (R), absolute fraction of variation (R^2), root mean square error (RMS) and coefficient of variance (COV) values, which can be calculated by using following equations.

$$R(a,p) = \frac{Cv(a,p)}{\sqrt{Cv(a,a)Cv(p,p)}} \times 100 \tag{3}$$

Here, $Cv(a,p)$ is the covariance between the actual and predicted output sets. It is given by

$$Cv(a,p) = E[(a-\mu_\mathrm{a})(p-\mu_\mathrm{p})^2] \tag{4}$$

Here, E is the expected value, a is the actual output, p is the ANN predicted output, μ_a is the actual mean value, μ_p is the ANN predicted mean value. The covariance of actual and predicted outputs are given by

$$Cv(a,a) = E[(a-\mu_\mathrm{a})^2] \tag{5}$$

$$Cv(p,p) = [(p-\mu_\mathrm{p})^2] \tag{6}$$

The fraction of absolute variance is given by

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(y_{\mathrm{pre},m} - t_{\mathrm{mea},m})^2}{\sum_{m=1}^{n}(t_{\mathrm{mea},m})^2} \tag{7}$$

The root mean square value is calculated by

$$\mathrm{RMS} = \sqrt{\frac{\sum_{m=1}^{n}(y_{\mathrm{pre},m} - t_{\mathrm{mea},m})^2}{n}} \tag{8}$$

Coefficient of variance is calculated by the following equation

$$\mathrm{COV} = \frac{\mathrm{RMS}}{\sum_{m=1}^{n}(t_{\mathrm{mea,avg}})} \times 100 \tag{9}$$

Here, n is the number of data patterns in the independent data set, $y_{\mathrm{pre},m}$ indicates the values predicted by ANN, $t_{\mathrm{mea},m}$ is the measured value of one data point m and $t_{\mathrm{mea,avg}}$ is the mean value of all measured data points.

3.4. Optimization of network architecture

Optimization of network architecture is the major task in ANN. The parameters that affect the performance of network are number of neurons in the hidden layer, number of hidden layer, transfer function, training algorithm, momentum factor and learning rate. The network architecture can be optimized by varying the above parameters (using trial and error method) to achieve the results with good accuracy.

4. Reviewing applications of ANN for RACHP systems

A summary of applications of ANN in the field of RACHP systems are discussed in this section. This section is divided into eight subsections based on the applications as follows: (i) vapour

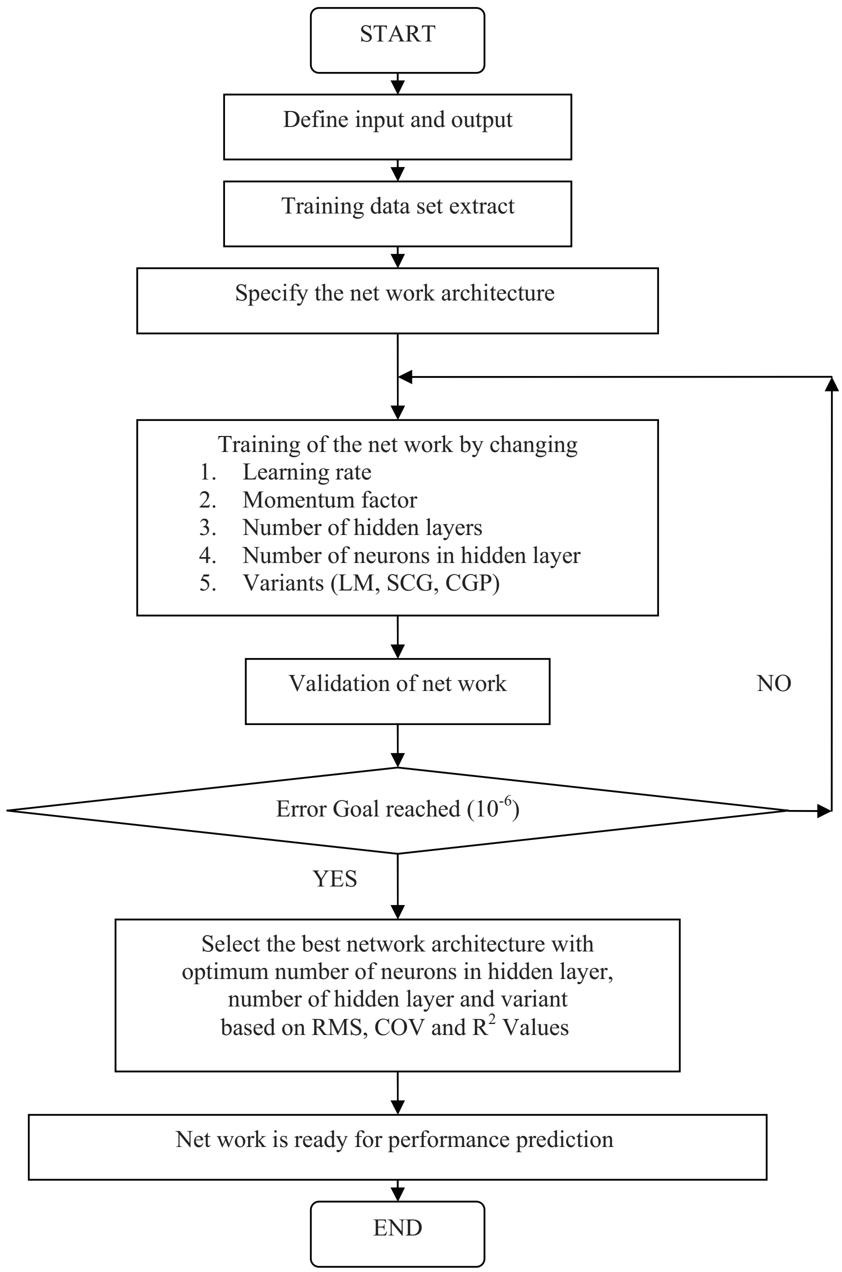

Fig. 6. Flow chart of ANN training processes [1,2].

compression systems, (ii) RACHP system components, (iii) vapour absorption systems, (iv) prediction of refrigerant properties (v) controlling of RACHP systems, (vi) phase change characteristics of refrigerants, (vii) HVAC systems and (viii) special purpose heating and cooling applications.

4.1. Vapour compression systems

The successful applications of ANN modeling for vapour compression based RACHP systems are discussed in this subsection. A summary of ANN applications for vapour compression systems are listed in Table 1.

4.1.1. Performance of refrigeration systems

Hosoz and Ertunc [12] studied the suitability of using MLFFN to predict the performance of a cascade refrigeration system. The inputs to the network are evaporator load and water mass flow rate, while the outputs are evaporating temperature, compressor power in lower circuit, COP for lower circuit, compressor power in higher circuit and overall COP for cascade refrigeration system. The network using Levenberg–Marguardt (LM) variant was optimized for a 2-4-5 (neurons in input-hidden–output layers) configuration. ANN predicted results were reported to be closer with experimental values having correlation coefficients of 0.996, 0.994, 0.97, 0.985, 0.953 for evaporating temperature, compressor power in lower circuit, COP for lower circuit, compressor power in higher circuit and overall COP of a cascade refrigeration system, respectively with corresponding mean relative errors of 0.2%, 3.6%, 3.6%, 3.9% and 6%.

A MLFFN with one neural in input layer (condenser water flow rate) and four neurons in output layer (input power in cooling and heating mode, COP of the system in both cooling and heating modes) was developed for predicting the performance of a variable cooling capacity mechanical cooling system [13]. It was reported that ANN (using 1-6-4 configuration) predicted results were closer to experimental results with average relative errors of 1.37%, 4.44%,

Table 1
Applications of ANN for vapour compression systems.

Authors [references]	Network architectures	Year	Equipment
Hosoz and Ertunc [12]	MLFFN	2006	Cascade refrigeration system
Yilmaz and Atik [13]	MLFFN	2007	Mechanical cooling system
Ertunc and Hosoz [14]	MLFFN	2006	Refrigeration system
Saidur et al. [15]	MLFFN	2007	Domestic refrigerators
Swider et al. [16]	GRNN	2001	Chillers
Navarro-Esbrı et al. [17]	RBFNN	2007	Chillers
Chang [18]	MLFFN	2007	Chillers
Atik et al. [20]	MLFFN	2010	Automobile air conditioners
Bacthler et al. [21]	GRBF	2001	Heat pumps
Arcaklioglu et al. [22]	MLFFN	2004	Heat pumps
Esen and Inalli [25]	MLFFN	2009	GSHP
Esen et al. [26]	ANN-SWP	2008	GSHP
Esen et al. [27]	ANFIS	2008	GSHP
Mohanraj et al. [28–30]	MLFFN	2009	DXSAHP

2.05%, 1.95% for input power, heating power, heating COP, and for cooling COP, respectively. The R^2 values for predicting the input power, heating power, heating COP and cooling COP are 0.992, 0.972, 0.988 and 0.990, respectively.

Ertunc and Hosoz [14] developed a MLFFN model with five neurons in input layer (representing evaporator load, air mass flow rate, water mass flow rate, dry bulb and wet bulb temperature of air at the condenser inlet) and five neurons in output layer (representing condenser load, mass flow rate of refrigerant, compressor power absorbed by the refrigerant, electric power consumed by the compressor motor and COP) for predicting the performance of a refrigeration system using an evaporative condenser. The network with 5-4-4 configuration yields correlation coefficient values of 1, 0.999, 0.998, 0.991 and 0.933 for condenser heat rejection rate, mass flow rate of refrigerant, compressor power, electric power input and COP, respectively with corresponding RMS errors of 4.12 W, 0.04 g/s, 2.41 W, 11.67 W and 0.18. The mean relative errors are in the range between 1.90% and 4.18%.

The energy consumption of refrigerators was predicted by using a MLFFN [15]. In their study, the energy consumption of 149 refrigerators was used for training. The energy performance of refrigerator was predicted with reference to eight parameters (such as capacity, door opening, loading, age, number of units, income, location and number of occupants). The network configuration 8-15-1 with log-sigmoid transfer function using LM training algorithm yields a maximum R^2 of 0.9999 with RMS and COV values of 0.0001 and 0.0034, respectively.

4.1.2. Performance of chillers

The performance of two vapour compression chillers (chiller-A and chiller-B) was predicted by using ANN [16]. They used GRNN model for predicting the performance parameters such as COP, compressor power input, chill water inlet and cooling outlet temperatures with reference to cooling capacity, chill water outlet and cooling water inlet temperatures. Their results showed that 94% of ANN predicted values for chiller-A and 87% for the chiller-B are within ±5% of the experimental values. The maximum COV of ANN predicted results for the chiller-A and chiller-B were reported as 1.7% and 3.9%, respectively. A RBFNN model was developed for predicting the performance parameters (such as cooling capacity, power consumption and chiller water outlet temperature) of a variable speed compression based refrigeration systems with reference to speed, chill water temperature inlet, condensing water temperature inlet and refrigerant evaporator temperature [17]. It was reported that the network predicted cooling capacity, chill water outlet temperature and power consumption were closer to experimental values within ±2%, ±0.2 K and ±5% deviations, respectively with RMS errors of 0.084, 0.054 and 0.048. Chang [18] reported the suitability of ANN model to determine the optimal sequencing of six chillers used in a semi conductor industry. In his work, MLFFN with four neurons in input layer (representing supply temperature of chill water, return temperature of chill water, supply temperature of cooling water and return temperature of cooling water), one neuron in the output layer (power consumption) was developed. Two hidden layers consisting of 20 and 40 neurons were used. It was reported that significant energy savings can be made by changing the chiller start-up sequences using ANN model.

4.1.3. Performance of automobile air conditioning systems

Hosoz and Ertunc [19] predicted the performance of an automobile air conditioning system using ANN. They developed a MLFFN for predicting the performance parameters such as compressor power, heat rejection rate in the condenser, refrigerant mass flow rate, compressor discharge temperature with reference to compressor speed, cooling capacity and condensing temperature. It has been reported that MLFFN (with 3-5-4 configuration) using LM variant predicts the performance values closer to experimental values with good correlation coefficient values in the range of 0.968–0.999, mean relative errors in the range of 1.52–2.51% with very low RMS errors. The results proved that performance of an automobile air conditioning systems can alternatively predicted by using ANN with good accuracy. Similarly, Atik et al. [20] developed a MLFFN for predicting the performance parameters (such as cooling capacity, power consumption and COP) of an automobile air conditioner with reference to refrigerant charge quantity and compressor speed. The network having a 2-10-3 configuration predicts the cooling capacity, power consumed and COP with good R^2 values of 0.945, 0.985 and 0.994, respectively. The mean relative errors between experimental and ANN results for predicting the cooling capacity, power consumption and COP were reported as 6.806%, 8.244% and 4.403%, respectively.

4.1.4. Performance of heat pumps

Bechtler et al. [21] used generalized radial basis function (GRBF) neural network for predicting the steady-state performance of a vapour-compression liquid heat pump. The COP of a heat pump using R22, LPG and R290 was predicted with reference to chilled water outlet temperature from the evaporator, cooling water inlet temperature to the condenser and evaporator capacity. The predictions of COP values, when R22 or LPG was used as refrigerant are within 2% deviation compared to experimental values, whereas COP predictions for R290 deviate more than ±10%.

The performance of a heat pump with different mass ratios of refrigerant mixture R12/R22 was predicted using ANN [22]. They developed a MLFFN model with three neurons in input layer representing mixture ratio, refrigerant temperature entering the evaporator and condenser pressure, and two neurons in output layer representing COP and rational efficiency. Three variants such

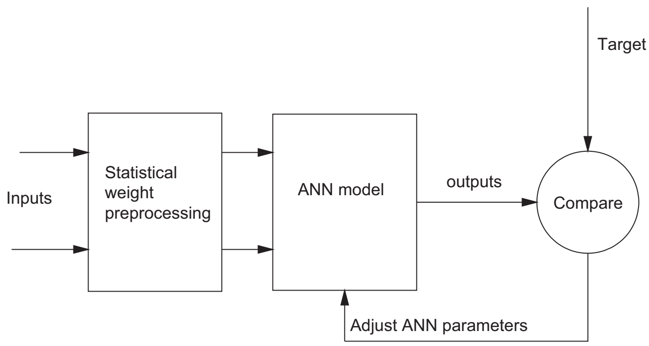

Fig. 7. Structure of ANN and SWP hybrid model [26].

as Levenberg–Marguardt (LM), Conjugate Gradient Pola–Ribiere (CGP), and Scaled Conjugate Gradient (SCG) with log sigmoid transfer function were used in their work. The network predictions of COP and rational efficiency are closer to experimental results with R^2 of 0.9999. They also reported that LM variant will provides better results compared to CGP and SCG. In similar work, Arcaklioglu [23] predicted the performance parameters of the system (COP and total irreversibility) using environment friendly alternative refrigerants. He developed a MLFFN with seven neurons in the input layer representing the mixture ratios of R32, R125, R134a, R143a, R152a, R290 and R600a and two neurons in the output layer representing the COP and total irreversibility. Three learning algorithms such as SCG, CGP and LM with logistic sigmoid transfer function were used in his work. The number of neurons was varied between 23 and 26. His results confirmed that LM algorithm with 24 neurons in the hidden layer yields a maximum correlation coefficient of 0.9999 with maximum error less than 2–3% and root mean square error less than 0.002.

ANN technique was successfully applied for predicting the performance of a horizontal and vertical ground source heat pump [24,25]. In their study, COP was predicted with reference to three parameters such as air temperature entering condenser unit, air temperature leaving condenser unit and ground temperatures (at 1 and 2 m depth) in input layer. The back propagation learning algorithm using three different variants, namely LM, CGP, and SCG with tangent sigmoid transfer function were used in the network. It was reported that LM learning algorithm with 3-7-1 configuration predicts the COP closer to experimental results with RMS value of 1%, R^2 value of 99.99% and COV of 28.62% for horizontal ground source heat pump. In further study, Esen et al. [26] forecasted the performance of ground source heat pump using ANN with a statistical weighted pre-processing (SWP) method, which is depicted in Fig. 7. In the first stage, normalization of the input data set is conducted and normalized data are weighted in the interval [0,1] using SWP. After this pre-processing step, the weighted data set was presented to the main modeling unit. The second stage uses ANN to model weighted data. The model has five input variables such as air temperature entering and leaving the condenser unit, water-antifreeze solution entering and leaving the horizontal ground heat exchanger and ground temperature with one output variable (COP). Their results reported that RMS, R^2 and COV of the network are 0.074, 0.9999 and 2.22, respectively for ANN structure using SCG6 algorithm, whereas for SCG6 algorithm of SWP-ANN structure, it was reported that RMS, R^2, and COV values are 0.002, 0.9999 and 0.076, respectively. The faster and simpler solutions were reported by using hybridized ANN model with SWP. Esen et al. [27] compared the performance prediction of geothermal heat pump using ANN and ANFIS. ANN model using LM algorithm with seven neurons in the hidden layer yields R^2 value of 0.9999 with RMS and COV values of 0.0100 and 0.2862, respectively. Whereas ANFIS predicts the COP with R^2 of 0.9999, RMS value of 0.0047 and COV of 0.1363. The accuracy of results predicted using ANFIS was reported better than conventional ANN model.

Mohanraj et al. [28] developed an ANN model for energy performance prediction of a direct expansion solar assisted heat pump (DXSAHP). In their study, the performance parameters such as energy performance ratio, heating capacity, compressor discharge temperature and power consumption were predicted with reference to solar intensity and ambient temperature. ANN model using LM variant was optimized for 2-10-4 configuration. The network predictions of energy performance ratio, heating capacity, compressor discharge temperature and power consumption were closer to experimental values with RMS error values of 0.0075, 17.28 W, 0.2258 °C and 5.6 W, respectively and R^2 values of 0.9999 for all predictions. Similarly, ANN modeling was also successfully applied for predicting the exergy destruction and exergy efficiency of a DXSAHP [29,30]. They developed two ANN models for predicting the exergy destruction and exergy efficiency of each component of the system with reference to solar intensity and ambient temperature. The two ANN models using LM variant were optimized with 2-12-5 configuration. ANN predictions were reported to be closer with experimental results with correlation coefficient values of 0.9938, 0.9898, 0.9930, 0.9779 and 0.9933 and COV values of 1.53, 1.043, 0.0292, 0.9887 and 0.4361 for exergy destruction in compressor, condenser, expansion valve, solar collector and for the overall system, respectively. Similarly the exergy efficiencies are closer to experimental results with correlation coefficient values of 0.9891, 0.9957, 0.999, 0.9517 and 0.9472 and COV values of 0.372, 0.7996, 0.0029, 1.2418 and 1.5624 for compressor, condenser, expansion valve, solar collector and for the overall system, respectively. The studies cited in this subsection confirmed that ANN predictions of energy and exergy performance of compression refrigeration systems are acceptable.

4.2. RACHP system components

The applications of ANN models for performance prediction of RACHP system components such as compressors, condensers, cooling towers and capillary tube are discussed in this subsection. Table 2 summaries the ANN applications for RACHP system components.

4.2.1. Modeling of refrigerant compressors

Two ANN models were developed for predicting the volumetric and isentropic efficiency of refrigerant compressors [31]. In the first model, two neurons in input layer representing condensation temperature and pressure ratio for predicting the volumetric efficiency. In the second model, two neurons in the input layer represent the condensation and evaporator temperature for predicting the isentropic efficiency. The second-order polynomial transfer function was used in the hidden layer for predicting volumetric efficiency and the third order polynomial transfer function was used in the hidden layer for predicting isentropic efficiency. They reported that polynomial transfer function is more effective in training and free of over-learning. The pure linear transfer function is used in output layer of the two neural networks. The network predictions of volumetric and isentropic efficiencies are less than 0.4% standard deviations and within ±1.3% maximum deviations against the manufacturer data. Similarly, Sanaye et al. [32] developed a thermal model of a rotary vane refrigerant compressor using ANN. They developed a MLFFN with four neuron in input layer (representing the speed of compressor, suction pressure, discharge pressure and suction temperature) and two neurons in output layer (representing discharge temperature and mass flow rate). It was reported that network predictions are closer to experimental values with R

Table 2
Applications of ANN for RACHP components.

Authors [references]	Network architectures	Year	Component
Yang et al. [31]	MLFFN	2009	Refrigerant compressors
Islamoglu [33]	MLFFN	2003	Wire on tube condensers
Hayati et al. [34]	ANFIS	2009	Wire on tube condensers
Ertunc and Hosoz [35]	ANFIS	2008	Evaporative condensers
Zhao and Zhang [36]	MLFFN	2010	Fin and tube condensers
Pacheco-Vega et al. [37]	MLFFN	2001	Finned tube heat exchangers
Yigit, and Ertunc [38]	MLFFN	2006	Cooling coils
Islamoglu et al. [39]	MLFFN	2005	Capillary tube suction heat exchanger
Vins and Vacek [44]	MLFFN	2009	Capillary tubes
Gao et al. [45]	MLFFN	2004	Cooling towers
Hosoz et al. [45]	MLFFN	2009	Evaporative coolers

values in the range between 0.962 and 0.998, mean relative errors in the range between 2.79% and 7.36%. The root mean square errors for predicting refrigerant mass flow rate and compressor discharge temperature are 10.59 kg/h and 12 K, respectively.

4.2.2. Performance of refrigerant condensers

Islamoglu [33] predicted the heat transfer rate of a natural convection wire on tube heat exchanger (commonly used in domestic refrigerators) using MLFFN with reference to 12 parameters (such as area of tube, area of wire, diameter of tube, diameter of wire, length of the tube, length of the wire, mass flow rate of refrigerant, temperature of the refrigerant at the inlet, volumetric flow rate of air, temperature of air at condenser inlet, total area of tube and wire, condensation temperature of refrigerant). The network with 12-5-1 configuration predicts the heat transfer values with maximum relative errors were approximately 5.56% and 7.94% for training and testing, respectively. Similarly, the heat transfer rate of a wire on tube heat exchanger was predicted using ANFIS and compared it with ANN [34]. The maximum relative error and mean relative errors using ANFIS were 8.98% and 2.54%, respectively. On the other hand, ANN model has maximum relative error of 7.94% and mean relative error of 4%. The results obtained with ANFIS are reported to be more reliable and accurate compared to ANN model.

Ertunc and Hosoz [35] compared the performance predictions of an evaporative condenser using MLFFN and ANFIS techniques. They predicted the condenser heat rejection rate, refrigerant temperature leaving the condenser along with dry and wet bulb temperatures of the leaving air stream with reference to seven parameters (such as dry bulb and wet bulb temperatures of air at inlet to the condenser, mass flow rate of air, mass flow rate of refrigerant, mass flow rate of water, absolute pressure and temperature of the refrigerant at the inlet to the condenser). Their results confirmed that both ANN and ANFIS predictions are within $\pm 5\%$ deviations with experimental values. The accuracy of ANFIS predictions was reported to be better than that of ANN predictions. The performance of a fin and tube air cooled condenser was predicted using ANN [36]. In their work, two modeling approaches are chosen and compared to each other. One is multi input single output (MISO) approach (means the multi input multi output (MIMO) problem is separated into three MISO problems for ANN training and afterwards the trained MISO models are combined into a single MIMO network). Another is MIMO approach, which is modeled directly. The inputs of the network are refrigerant flow rate, air-flow rates, refrigerant inlet temperature and saturated temperature, and entering air dry-bulb temperature. Outputs of the network consist of heating capacity and pressure drops on both refrigerant and air sides. Their results indicated that the MISO approach requires less training data than the MIMO, which becomes more valuable when the training data are extracted from experiments. The deviations of the heating capacity, the refrigerant-side and air-side pressure drops predicted by both MISO and MIMO are with in $\pm 5\%$ compared to experimental values.

Pacheco-Vega et al. [37] developed MLFFN with eleven neurons in input layer and one neuron in output layer for predicting the heat transfer rate of a finned tube refrigerant heat exchanger. In their study, the heat transfer rate was predicted with reference to eleven parameters such as mass flow rate of air, dry bulb temperature of air, humidity ratio, inlet refrigerant temperature, fin spacing, width, number of rows, number of columns, number of circuits, tube spacing in longitudinal and transverse directions. The network with 11-11-7-1 configuration was reported as an optimum topology. Three test experiments selected in the small, medium and large error range were selected for comparison. For the first test, the estimated error was determined as 0.761% while the actual error was 0.112%. The second test gave estimated and actual errors as 23.3% and 6.19%, respectively, while the 48.78% and 14.21% were the values for the third one. In similar work, ANN technique was used to predict the temperature and humidity of air at the outlet of a wire-on-tube type cooling coil using ANN [38]. They developed ANN model with nine neurons in the input layer (representing temperature and humidity of the air entering the coil, air velocity, frost weight, the temperature at the coil surface, mass flow rate of the heat transfer fluid and its temperatures at the inlet and outlet of the coil along with ambient temperature) and two neuron in out put layer (representing air temperature and humidity at the outlet). The ANN predictions yield a maximum correlation coefficient of 0.999 and 0.982 for temperature and humidity at the outlet of the coil with errors of 1% for outlet air temperature and 2% for outlet humidity.

4.2.3. Capillary tube suction line heat exchanger

Islamoglu et al. [39] used a MLFFN model using the back propagation learning algorithm to predict the temperature and refrigerant mass flow rate of a non-adiabatic capillary tube suction line heat exchanger used in small household refrigeration systems. They developed a MLFFN with seven neurons in input layer (represents sub cooling, suction line inlet temperature, internal diameter of a capillary tube, internal diameter of the suction line, length of the capillary tube, length of the heat exchanger and adiabatic inlet length) and two neurons in output layer (refrigerant suction line outlet temperature and mass flow rate). It was reported that network with 7-7-2 configuration predicts the refrigerant suction line outlet temperature and mass flow rate of refrigerant with mean relative error of 1.94% and 2.26%, respectively compared to experimental results.

4.2.4. Mass flow rate of refrigerant through the capillary tubes

A generalized ANN based correlation for predicting the mass flow rate of refrigerant through the capillary tube was developed by Zhang [40]. The network with seven neurons in the input layer (represent the seven dimensionless terms such as inlet pressure, sub

cooling, geometry, density, friction, bubble growth, vapourisation) and one dimensionless parameter in the output layer (represent the mass flow rate) was developed using dimensional analysis. They trained and tested the network for different fluids such as R12, R134a, R22, R290, R407 C, R410A, and R600a available in the open literature. Their results reported that network with just one neuron in the hidden layer yields good statistical performance values with average and standard deviations of 0.4 and 6.6%, respectively for predicting the mass flow rate. In further work, Zhao et al. [41] developed an ANN based generalized correlation for predicting the mass flow rate of refrigerant through adiabatic capillary tubes. A MLFFN with 5-2-1 configuration predicts the mass flow rate with average and standard deviations of 0.75% and 8.27%, respectively. Yang and Zhang [42] also developed an ANN based correlation for predicting the mass flow rate of refrigerants through adiabatic capillary tubes. They developed MLFFN with five neurons in input layer (representing five non dimensional parameters). The trained MLFFN with 5-6-1 configuration will predict the mass flow rate of R12, R22, R134a, R290, R410A and R404A within deviations of $\pm$10%.

A modified dimensionless neural network correlation of refrigerant mass flow rates through adiabatic capillary tubes and short tube orifices with extension to CO_2 trans-critical cycle was developed [43]. In their network, the mass flow rate was predicted with reference to four dimensionless parameters. It was reported that network with 4-3-1 configuration predicts the mass flow rate of CO_2 with average and standard deviations for carbon dioxide mass flow rate are -2.5% and 6.0%, respectively. More than 90% of data fall into $\pm$10% error band. In a similar work, Vins and Vacek [44] developed a correlation for predicting the mass flow rate of refrigerant (R218) through the capillary tube using ANN and dimensionless analysis. They compared the ANN predicted mass flow rate with experimental results and results obtained from power law function. In the case of the ANN, seven dimensionless parameters (π_1–π_7) are considered as inputs and parameter π_8 is solved as a single-output. ANN correlation with two neurons in the hidden layer was reported as more precise with an average and standard deviations of -0.12% and 3.45%, respectively. Whereas the average and standard deviations of correlated data with the power law function are -0.41% and 4.85%, respectively. Their results confirmed that ANN predictions are closer to experimental values compared to power law function.

4.2.5. Performance of cooling towers

Hosoz et al. [45] predicted the performance of a cooling tower by using MLFFN. In their network, five neurons used in input layer represents the dry bulb temperature, relative humidity of the air stream entering the tower, temperature of water entering the tower, air volume flow rate and water mass flow rate, whereas the outputs are heat rejection rate in the cooling tower, mass flow rate of makeup water, temperature of water at tower outlet, dry bulb temperature and relative humidity of air stream leaving the tower. The network predictions were closer to the experimental values with correlation coefficients of 0.992, 0.981, 0.994, 0.994 and 0.975 for heat rejection rate in the cooling tower, the mass flow rate of makeup water, the temperature of the water at the tower outlet and the dry bulb temperature and relative humidity of the air stream leaving the tower, respectively with root mean square error of 43.83 W, 0.09 kg/h, 0.31 °C, 0.31 °C and 0.78%. The mean relative error was reported in the range between 0.89% and 4.64%. In similar work, Gao et al. [46] predicted the thermal performance of a natural draft counter flow cooling tower under crosswind conditions. The parameters such as circulating water outlet temperature, temperature difference and cooling efficiency of the cooling tower were predicted with reference to dry bulb temperature of inlet air, wet-bulb temperature, circulating water inlet temperature, circulating water inlet mass flow rate, and inlet air velocity. The network with 5-6-3 configuration predicts the performance of the cooling tower with correlation coefficients of 0.999, 0.998 and 0.995 for temperature at the outlet, temperature difference and efficiency of the cooling tower, respectively with corresponding RMS error of 0.044, 0.066 and 0.53.

4.2.6. Performance of an evaporative cooler

Hosoz et al. [47] successfully used ANN technique for predicting the performance parameters (such as dry bulb temperature, relative humidity of the leaving air, mass flow rate of the water evaporated into the air stream, sensible cooling rate, and effectiveness) of an evaporative cooler with reference to dry bulb temperature, relative humidity of the air stream entering the cooler, water mass flow rate, and air volume flow rate. The MLFFN with 4-4-5 configuration using LM variant predicts the performance parameters with correlation coefficients in the range of 0.969–0.993 with mean relative errors in the range of 0.66–4.04%, and absolute fraction of variance in the range between 0.9998 and 1.000.

4.3. Absorption refrigeration systems

Thermodynamic analysis of absorption thermal systems is too complex because it involves more analytic functions [48]. ANN has been successfully used in modeling of absorption systems. The studies reported with application of ANN for modeling of absorption systems are discussed in this subsection. Table 3 shows a summary of ANN applications for vapour absorption systems.

4.3.1. Performance of an absorption system

The performance of an ejector absorption heat pump using two refrigerant-absorbent pairs (such as lithium bromide-methanol and lithium chloride-methanol) was predicted by using MLFFN [49,50]. The back propagation learning algorithm with three different variants such as (LM, SCG and CGP) and logistic sigmoid transfer function were used in their work. The network configuration 4-8-3 (using LM variant) was reported as the most suitable for performance prediction. The deviations between the ANN and experimental results for predicting COP, exergitic COP (ECOP) and circulation ratio (*F*) for all working temperatures were reported to be less than 1.8%, 4%, 0.2%, respectively for Lithium bromide-methanol pair and 1.7%, 5.1% and 1.8% for lithium chloride-methanol pair, respectively. In further work, Sozen and Akcayol [51] successfully applied an ANN technique for predicting performance parameters (such as COP, ECOP and *F*) of a solar driven aqua-ammonia ejector absorption refrigeration cycle. They developed MLFFN with four neurons in the input layer (representing generator temperature, evaporator temperature, absorber temperature and condenser temperature) and three neurons in output layer (performance parameters). They trained the network with generator temperature (in the range of 50–130 °C), evaporator temperature (between -10 and 10 °C), condenser temperature (as 25, 30 and 35 °C) with absorber temperature (as 30, 35 and 40 °C). The network predicts the COP, ECOP and *F* values with a correlation coefficient of 0.976, 0.9825, and 0.9855, respectively.

A MLFFN model was developed for predicting the performance of a double effect absorption chiller using steam as heat input [52]. The model will predict the COP of the system with reference to six parameters such as time, chilled water inlet and outlet temperatures, cooling water inlet and outlet temperatures and steam pressure. The network was trained with one year of experimental data. MLFFN with 6-6-9-1 configuration predicts the performance within $\pm$1.2% of the experimental values with fraction of variance of 0.9997. Sencan [53,54] predicted the performance of ammonia–water absorption refrigeration (AWAS) systems using ANN. In his work, MLFFN with six neurons in the input layer and

Table 3
Applications of ANN for absorption systems.

Authors [references]	Network architectures	Year	Absorption system
Sozen et al. [49]	MLFFN	2004	Ejector absorption refrigeration system
Manohar et al. [52]	MLFFN	2006	Double effect absorption chiller
Rosiek and Batlles [55]	MLFFN	2010	Solar absorption air conditioner
Sozen and Arcaklioglu [56]	MLFFN	2007	Exergy analysis of Ejector absorption system
Chow et al. [57]	MLFFN	2002	Global optimization of absorption chillers

two neurons output layer was developed. The evaporator temperature, absorber temperature, condenser temperature and generator temperature, poor and rich solution concentrations are the input data and circulation ratio and COP of AWRS are the actual output of the network. Two variants of the algorithm such as LM and SCG were used in their network. The results showed that LM algorithm with five neurons in the hidden layer yields a good correlation coefficient of 0.9996 and 0.9873 for the circulation ratio and COP, respectively. The performance of a solar assisted single-effect lithium bromide–water absorption air-conditioning system was predicted by using MLFFN [55]. The input layer includes the entering generator temperature, leaving generator temperature, entering evaporator temperature, leaving evaporator temperature, incident radiation intensity, leaving flat-plate collectors temperature and collectors mass flow rate. The output layer has four nodes, which includes COP, cooling capacity and global system efficiency 1 and 2. The MLFFN with 8 neurons in the hidden layer predicts the performance parameters such as COP, cooling capacity, global system efficiency 1 and global system efficiency 2 with a correlation coefficient of 0.9985, 0.998, 0.998 and 0.999, respectively. The root mean square error values of all the above predictions are reported less than 1.9%.

4.3.2. Exergy losses of an ejector absorption heat transformer

Sozen and Arcaklioglu [56] proposed a MLFFN for determining the non dimensional exergy losses of ejector absorption heat transformer (components of the system such as generator, condenser, evaporator and an absorber) with reference to system operating temperatures (such as generator temperature, condenser temperature, evaporator temperature and an absorber temperature). Two variants such as SCG and LM with log sigmoid transfer function were used. It was reported that network using SCG variant with seven neurons in the hidden layer yields a correlation coefficient of 0.9940, 0.9996 and 0.9993 with RMS error values of 0.01515, 0.0210 and 0.00817 for the non-dimensional exergy losses of generator, absorber and condenser, respectively. The LM variant with seven neurons in the hidden layer gave the best correlation coefficient of 0.9997 with RMS error of 0.006866 for non dimensional exergy loss in evaporator.

4.3.3. Global optimization of absorption chillers

Chow et al. [57] optimized the use of fuel and electricity in a direct fired absorption chiller system using ANN and genetic algorithm. They developed a MLFFN with five variables in the input layer representing mass flow rate of chill water (used in evaporator), mass flow rate of cooling water (used in condenser), temperature of chill water leaving the chiller unit, temperature of the cool water entering the chiller unit and the cooling capacity. The output layer consists of four neurons namely COP, fuel consumption rate, power consumption of the chill water pump and power consumption of the cooling water pump. The results reported that MLFFN with 5-5-9-4 configuration yields correlation coefficient values of 4.94%, 5.64%, 7.91% and 7.24%, respectively for COP, fuel consumption rate, power consumption of the cooling water pump and power consumption of chill water pump, respectively with mean square error value of 0.00285.

4.4. Properties of refrigerants

Determination of refrigerant properties needs high measuring technology, which is more expensive, whereas, theoretical predictions involve more complicated analytical equations. ANN has been successfully used for predicting the thermodynamic properties of pure and mixed refrigerants [58]. The studies reported with the use of ANN for predicting the properties and vapour–liquid equilibrium (VLE) of refrigerants are discussed in this subsection. Table 4 presents the applications of ANN for predicting the properties of refrigerants.

4.4.1. Prediction of refrigerant properties

ANN was successfully applied for predicting the thermodynamic properties such as specific volume, enthalpy and entropy in both saturated liquid–vapour region and superheated vapour region for three refrigerant mixtures such as R404A, R407C and R508A [59–61]. They developed two ANN models for predicting properties in saturated liquid-vapour and superheated region. It has been reported that ANN model will reduce the experimental uncertainties and also eliminating the need of analytic equations. ANN predicted results are closer to experimental values with good correlation coefficients of 0.9999 and low RMS values in both wet-vapour region and superheated region. Their results confirmed that use of ANN for predicting the properties of azeotropic, zeotropic and near azeotropic mixtures are quite suitable.

ANN model for predicting the viscosity of R152a was reported by Scalabrin and Cristofoli [62]. They developed MLFFN with two neurons in input layer (representing reduced temperature and reduced density) and one neuron in the output layer (representing viscosity). The network with eight neurons in the hidden layer predicts the viscosity values with an average absolute deviation values ranging from 0.36% to 0.49%. In similar work, Mohebbi et al. [63] predicted the saturated liquid density of nineteen pure refrigerants and six mixed refrigerants using ANN based genetic algorithm. In their work, the numbers of neurons in hidden layer, the momentum and the learning rates have been optimized using genetic algorithm to minimize the time and effort required to find the optimal network architecture. They developed a MLFFN with two neurons in input layer representing (acentric factor and reduced temperature) and one neuron in output layer representing reduced liquid density. The results obtained are compared with the experimental data, Hankinson and Thomson and Riedel methods, and Spencer and Danner modification of Rackett methods. It has been reported that the average of absolute percent deviation are 1.46 and 3.53 for 14 pure and 6 mixed refrigerants, respectively. They concluded that genetic algorithm based ANN is more efficient compared to conventional trial and error method.

Sencan et al. [64] used ANN model to determine the thermo physical properties of five refrigerant mixtures such as R413A, R417A, R422A, R422D and R423A. They developed MLFFN with three input neurons (representing temperature, liquid pressure

Table 4
Applications of ANN for predicting properties of refrigerants.

Authors [references]	Network architectures	Year	Properties
Sozen et al. [61]	MLFFN	2010	Specific volume, enthalpy and entropy
Scalabrin and Cristofoli [62]	MLFFN	2003	Viscosity
Mohebbi et al. [63]	MLFFN	2008	Saturated liquid density
Sencan et al. [64]	MLFFN	2011	Thermo-physical properties
Kurt and Kayfeci [66]	MLFFN	2009	Thermal conductivity of liquids
Eslamloueyan and Khademi [67]	MLFFN	2009	Thermal conductivity of gases
Sozen et al. [68]	MLFFN	2004	Refrigerant absorbent pairs
Mohanty [72]	MLFFN	2006	Vapour–liquid equilibrium

and vapour pressure) and seven output neurons (representing liquid and vapour heat conduction coefficient, dynamic viscosity, kinematic viscosity, thermal diffusivity, density and specific heat capacity) with eleven neurons in the hidden layer. The mathematical formulations have been obtained from the summation and activation functions used in the ANN model and the weights of the neurons. It was reported that property values calculated from the ANN formulations were closer to experimental results. The thermo physical properties such as vapour pressure and densities of dimethyl ether (RE170) were estimated by using ANN [65]. Two ANN models were developed (one for predicting the vapour pressure and another for predicting the density of RE170). The ANN model with two neurons in input layer representing temperature and pressure, two hidden layers with twelve and fifteen neurons and one neuron in output layer representing density. Another model with one neuron in input layer (temperature), one neuron in output layer (vapour pressure) and one hidden layer having two neurons was developed. The uncertainties reported in their network for predictions of vapour pressure and density are less than 0.04% and 0.16%, respectively.

Kurt and Kayfeci et al. [66] predicted the thermal conductivity of ethylene glycol–water solution (widely used secondary refrigerant solution in the commercial air conditioning chillers) using MLFFN with reference to temperature, density and concentration. They developed the network with three neurons in input layer and one neuron in output layer for predicting the thermal conductivity. The network with 3-4-1 configuration predicts the thermal conductivity with a regression coefficient of 0.9999.with mean absolute percentage error of 0.7984%. Similarly, the thermal conductivity of the refrigerant gas was predicted by using MLFFN [67]. They trained the network for wide range of temperatures, critical temperatures, critical pressures and molecular weights to predict conductivity of pure gases at atmospheric pressure. A set of 236 experimental data points for hydrocarbon and non-hydrocarbon compounds was used for training the network. The network with 4-10-1 configuration predicts the thermal conductivity of the gases with good accuracy.

4.4.2. Prediction of refrigerant-absorbent pairs

Sozen et al. [68,69] presented MLFFN approach for predicting the thermodynamic properties of two alternative refrigerant/absorbent couples (methanol–LiBr and methanol–LiCl). The back-propagation learning algorithm with three different variants (such as LM, CGP, SCG) and logistic sigmoid transfer function were used in their network. The input layer of represents the temperatures (in the range of 298–498 K) pressures (in the range between 0.1 and 40 MPa) and concentrations of 2%, 7%, and 12% of the couples are specified. The output layer represents the specific volume of the mixture. The network with 3-8-1 configuration using SCG variant yields correlation coefficient of 0.9999 with maximum error of 2.22% and RMS values of 0.00161 and 0.000372 for methanol–lithium bromide and methanol–lithium chloride refrigerant–absorbent pairs, respectively. Sencan et al. [70] predicted the enthalpy of lithium chloride–water and lithium bromide–water (absorbent–refrigerant pairs) using ANN. They developed two MLFFN with two neurons in input layer (representing the concentration and temperature) and one neuron in output layer (representing the enthalpy of absorbent–refrigerant pair). The network configuration 2-4-1 and 2-8-1 was reported as the most optimal topology for predicting the enthalpy of lithium chloride–water and lithium bromide water combinations, respectively. It was reported that the coefficient of multiple determination between the experimental and ANN predicted data is about 0.999 for the enthalpy of both lithium bromide-water and lithium chloride–water solutions.

4.4.3. Vapour–liquid equilibrium predictions

Urata et al. [71] developed an ANN model for predicting the vapour–liquid equilibrium (VLE) for binary systems containing hydrofluroethers (used as refrigerants) in three steps. In the first step, the sign of logarithm of activity coefficient is estimated for each binary system using ANN. In the second step, two sets of relation between liquid mole fraction and logarithm of activity are constructed. In the third step, vapour–liquid composition and equilibrium temperature are calculated using the estimated activity coefficient. The input parameters for the first ANN are normal boiling point divided by molecular weight, density and dipole moment for both the components and the output is a negative or positive sign. The second ANN has an extra input of mole fraction of one of the components in the liquid phase in addition to the inputs of the first ANN. The output from the second ANN is the logarithm of the activity coefficient for that component. Using the logarithmic activity coefficients, vapour–liquid composition and equilibrium temperature were calculated. The network predictions for the first network yield a correlation coefficient of with 0.984 and the average of absolute deviation was 0.098. For the second network, the correlation coefficient and absolute deviation are 0.988 and 0.014, respectively. Mohanty [72] estimated VLE of a refrigerant mixture (carbon dioxide–difluoromethane) using ANN. In their work, a MLFFN with two neurons in input layer (representing temperature and pressure or temperature and liquid phase composition) and two neurons in output layer (liquid and vapour phase composition or vapour phase composition and pressure) with one hidden layer (having ten neurons) was developed. Experimental data in the temperature range 222.04–343.23 K and pressure range from 0.105 to 7.46 MPa were taken from literatures were used as training and testing data for the ANN model. The network yields a correlation coefficient of 0.9991 and 0.999 for the equilibrium pressure and mole fraction of CO_2 in the vapour phase, respectively.

4.5. Control of RACHP systems

The controlling of components in RACHP systems plays a key role in achieving better performance under dynamic operating conditions. Conventional controllers cannot deal with nonlinear behavior of the systems that include uncertainties, time delays and limited operation point of refrigeration systems, which may reduce the energy efficiency. Nonlinear controllers based on fuzzy logic and ANN may overcome these issues [73]. The applications of

Table 5
Applications of ANN for control of RACHP systems.

Authors [references]	Network architectures	Year	Applications
Palau et al. [74]	MLFFN	1999	Gas sorption chilling system
Nanayakkaraa et al. [75].	RBFN	2002	Evaporator
Abbassi and Bahar [76]	MLFFN	2005	Evaporative condenser
Tse and Chan [77]	MLFFN	2005	Air handling unit
Soyguder [79]	WPD-NN	2011	Fan speed in HVAC system
Khayyam et al. [80]	MLFFN	2011	Automobile air conditioning systems

ANN in controlling the refrigeration and air conditioning systems are presented in this section. A summary of ANN applications for control of RACHP systems are listed in Table 5.

4.5.1. Control of a gas/solid sorption chilling system

Palau et al. [74] used ANN model to control the gas/sorption chilling system. The back propagation learning rule with sigmoid transfer function has been applied in feed forward neural network having a single hidden layer. In their work, five neural network models have been developed to predict the mean cooling power in stage 1 and stage 2, cycle time for stage 1 and stage 2 under different operating conditions and external source temperature. Cooling power in the stage 1 and 2, cycle time for stage 1 and stage 2 were predicted with reference to environment temperature (in the range between 278 and 303 K), and the external heat source temperature (in the range between 573 and 608 K). Due to the lack of experimental data, the network was trained with theoretically simulated data obtained from a computer simulation program. The RMS error for predicting the cooling power in the stage 1 and stage 2, cycle time for stage1 and stage 2 under different operating conditions and external source temperatures are 0.017, 0.0004, 0.011, 0.0003 and 0.0003, respectively.

4.5.2. Control of an evaporator

A novel RBFN architecture characterized by activation functions with dynamic synaptic units (DSU) was adopted in controlling the ammonia evaporator [75]. Two other neural network structures such as direct mapping neural network (DMNN) and RBFNN with dynamic neural units (DNN) were used for comparison. From the three dynamic networks used in their study, the neural networks with DSU needs less input and hidden layer nodes than conventional DMNN with nonlinear static activation functions and RBFNN with DNN. The RBFNN with DSU results in faster convergence in the training process to control the evaporator more effectively.

4.5.3. Control of an evaporative condenser

Abbassi and Bahar [76] presented a thermodynamic modeling of an evaporative condenser (under steady state and transient state conditions) for controlling the thermal capacity using ANN and compared the results with proportional integral derivation (PID) controller. They developed MLFFN architecture with five neurons in the input layer (represents the five parameters, which affects the performance of the evaporative condenser such as refrigerant condensing temperature, refrigerant mass flow rate, inlet air temperature, inlet specific humidity, water flow rate) and three neurons in the output layer (represents the performance parameters such as amount of water evaporated, condenser load and outlet specific humidity and temperature). Their results reported that ANN controller can able to minimize the process error better than PID controllers. They also concluded that ANN controller is a good substitute for PID controller.

4.5.4. Control the performance of an air handling unit

Air-conditioning systems are highly non-linear and it is difficult to maintain thermal comfort environments. A fully automatic data acquisition system using ANN was developed for controlling the performance of an air handling unit [77]. In their work, MLFFN model with ten input neurons, twenty neurons in the hidden layer and two neurons in the output layer was developed. Online field data captured using data acquisition from a real air conditioning plant was used as an input–output training data for the ANN. It was reported that most of the errors for predicting the supply air temperatures and return water temperature lied within ±5% and the maximum error was 5.79%. They concluded that ANN with the newly developed data acquisition system achieved good prediction of operating temperatures and having good controlling capability of an air conditioning system.

4.5.5. Control of an expansion valve and speed of compressor

Ekren et al. [78] studied the effects of different control methods such as PID, fuzzy logic and ANN in a vapour compression based chiller using variable speed compressor and electronic expansion valve. ANN controller showed lower power consumption of 8.1% and 6.6% than PID and fuzzy logic controllers, respectively. Out of three control methods, ANN control algorithm gave strong response to the disturbance effect in the system.

4.5.6. Control of fan speed in HVAC systems

The speed of fan in a HVAC system was controlled by using wavelet packet decomposition-neural network (WPD-NN) to reduce the energy consumption and compared it with PID controller [79]. The network consists of three inputs (such as set point temperature of evaporator, temperature difference between the evaporator set point and evaporator and the first derivation of the difference between the set temperature of evaporator and the evaporator temperature), with one output (represents the fan motor speed). The R^2 and RMS values for predicting fan motor speed are 0.9953 and 3.40, respectively. The results confirmed that WPD-NN predicts and controls the fan speed more accurately compared to PID controllers.

4.5.7. Control of an automobile air conditioning systems

An adaptive neural network tuned PID controller was developed by Khayyam [80] to control the automobile air conditioning system. The control system reported in their work manages the operation of evaporator, blower, fresh air and the gates to provide the optimum comfort temperature, indoor air quality with the minimum energy consumption. A MLFFN with two neurons in its input-layer (desired temperature and cabin room temperature), ten neurons in its hidden-layer, and three neurons in its output layer (proportional, integral and derivative gains) was developed in their work. The activation functions used in their work are sigmoid and linear in the hidden and output layers, respectively. It was reported that power consumption of automobile air conditioning system was reduced by about 14% compared to the conventional control methods. In similar work, the faults in an automotive air-conditioner blower were identified using noise emission signals and neural networks [81,82]. It consists of a data acquisition, feature extraction and fault classification. The noise emission signals are obtained from a condenser microphone was recorded by a data acquisition system. The signals are split into several wavelet nodes without losing their original properties by wavelet packet decomposition

and entropy criterion. Energy values were calculated from nodes used for feature extraction. The calculated energy values were used as inputs to neural network classifiers for identifying the fault conditions. In their work, the probabilistic neural network was used to verify the performance and compared with the conventional back-propagation neural network technique. Their studies confirmed that ANN technique can be successfully used to identify the faults quickly and accurately.

4.6. Phase change characteristics of refrigerants

The correct prediction of both condensation and boiling heat transfer coefficient of refrigerants is highly important for optimum design of condenser and evaporators. The conventional method of predicting the boiling and condensation heat transfer coefficients of refrigerant mixtures involves more assumptions and complicated equations, which is too difficult [83]. To overcome this drawback, many researchers used ANN for predicting the boiling and condensation heat transfer coefficients. The studies reported with ANN for predicting the heat transfer coefficient is discussed in this section. Table 6 summarizes the applications of ANN for predicting the boiling and condensation heat transfer coefficients.

4.6.1. Condensation heat transfer coefficients

The condensation heat transfer coefficient of a hydrocarbon refrigerant (R600a) was predicted by using MLFFN [84]. The network was developed with six neurons in input layer (mass flow rate, mean vapour quality, input vapour quality, output vapour quality, saturation temperature, temperature difference between pipe wall and condensing fluid) and two neurons in output layer (representing the heat transfer coefficient and Nusselt number). The tangent sigmoid function and linear function were used in hidden and output layer, respectively. The trained 6-5-2 network configuration using LM variant predicts the condensation heat transfer coefficient and Nusselt number with mean relative error of 3.97 and 3.99, respectively. In similar work, Balcilar et al. [85] predicted the condensation heat transfer coefficient and pressure drop of R134a inside the vertical smooth tubes using four ANN models (such as MLFFN, RBFN, GRNN and ANFIS). They developed the network with five input parameters (mass flux, heat flux, temperature difference between the tube wall and saturation temperature and average vapour quality) and two outputs (experimental condensation heat transfer coefficient and pressure drop). The results reported that MLFFN with 5-13-1 architecture and RBFN were reported to be in good agreement for predicting the experimental condensation heat transfer coefficient and pressure drop with their deviations being within the range of ±5% for all tested conditions.

4.6.2. Boiling heat transfer coefficients

A generalized correlation for predicting the flow boiling heat transfer coefficients of two pure fluids (R22 and R134a) and two mixed refrigerants (R407C and R410A) was developed by using ANN [86]. Four dimensionless parameters from existing generalized correlations are selected as inputs to the network, while Nusselt number is used as the output. A MLFFN with 4-8-1 configuration with log-sigmoid transfer function in hidden and output layer was used in their work. The network predicts average, mean, and root mean square deviations of 2.5%, 13.0% and 20.3%, respectively. About 74% of the deviations are within ±20%, which is much better than that of the existing generalized correlations. Similarly, Scalabrin et al. [87] developed a new correlation technique for predicting the flow boiling heat transfer coefficient of pure fluids using MLFFN. Heat transfer coefficients of eight pure fluids and a ternary refrigerant mixture were predicted in their work. The boiling heat transfer coefficients of the refrigerants are predicted with reference to five parameters such as reduced temperature, mass flow rate, heat flux, vapour quality and tube inner diameter using MLFFN. For the eight pure fluids (such as R11, R12, R22, R32, R134a, R290, R600a and argon) and the mixture (R407C), a total of 5236 data points have been considered for training and validation. Out of 5236 data points, 4803 data points were used for training with an overall absolute average deviation of 7.72% and a bias of −1.62%, while the remaining data points were used for validation. By excluding the two pure fluids (R12 and argon), the remaining 3791 data points with six pure fluids and the mixture (R407C) were used for training with average absolute error of 4.45% and a bias of −0.44%. The accuracy of the results predicted from ANN model was reported with acceptable error limits. In further work, Scalabrin et al. [88] developed two MLFFN for predicting the boiling heat transfer coefficient of mixed refrigerants. In first model, the controlling physical quantities are considered as inputs for predicting the heat transfer coefficient values of pure fluids. While in the second ANN model, the values of boiling heat transfer coefficient values of two individual pure fluid and mixture composition were considered as inputs for predicting the boiling heat transfer coefficient of mixed refrigerants. The boiling heat transfer coefficient values predicted using ANN has been reported with satisfactory accuracies for R290/R600a and R32/R134a mixtures.

4.7. HVAC applications

Many researchers proved that ANN-based predictive and adaptive thermal control strategies in HVAC applications are more encouraging than analytical strategies for improving thermal conditions with accurate controls and energy efficiency. The applications of ANN in the field of HVAC are discussed in this subsection. A summary of ANN applications for HVAC systems are listed in Table 7.

4.7.1. Energy consumption of a passive solar building

Kalogirou and Bojic [89] predicted the energy consumption of a passive solar building using ANN. In their work multilayer recurrent architecture using the standard back-propagation learning algorithm was developed with five neurons in input layer such as season (summer and winter), thickness of insulation, masonry thickness (15–60 cm), function (with heat transfer coefficient and without heat transfer coefficient) and time of day with one neuron in the output layer (energy consumption of the building in kWh). The results obtained in their network yields a correlation coefficient of 0.9991 for predicting the energy consumption, which was quite satisfactory compared with experimental results. The results reported that ANN method of prediction was found to be much faster than the dynamic simulation programs. Similarly, ANN model was developed by Aydinalp et al. [90] for predicting the energy consumption of a residential cooling system and compared with conventional methods such as engineering method and conditional demand analysis. It was reported that network predicts the energy consumption of residential cooling systems with a correlation coefficient of 0.909, which is significantly better compared to the conventional methods.

4.7.2. Computation of predicted mean vote (PMV)

The PMV represents thermal sensation on a standard scale of thermal feeling for a large group of persons in an indoor climate. The value of PMV index varies between −3 and +3, from cold to hot, respectively, where the null value of the PMV index means neutral. It is a function of two human variables like clothing insulation worn by the occupants, human activity and four environmental variables such as air temperature, air relative humidity, air velocity and mean radiant temperature [91].

A MLFFN model was developed for computing PMV of a HVAC system [92]. In their work, the network with six neurons in input

Table 6
Applications of ANN for phase change characteristics of refrigerants.

Authors [references]	Network architectures	Year	Applications
Demir et al. [84]	MLFFN	2009	Condensation heat transfer coefficients
Balcilar et al. [85]	ANFIS	2011	Condensation heat transfer coefficients
Wang et al. [86]	MLFFN	2006	Boiling heat transfer coefficient
Scalabri et al. [87]	MLFFN	2006	Boiling heat transfer coefficient

layer (representing air temperature, wet bulb temperature, globe temperature, air velocity, clothing insulation and human activity) and one neuron in the output layer (representing PMV index) was used. The experimental observations were made in an air conditioned room of size $3.6 \times 3.6 \times 7.7\,m^3$, and are used for training the network. The network predicted results showed good agreement between the PMV values calculated from the neural network, PMV model and Fangers PMV model. Recently, Moon and Kim [93] developed ANN based thermal control for creating comfort thermal environment in residential air conditioning buildings. In their study, MLFFN with eight neurons in input layer representing exterior air temperature, exterior air temperature change from the preceding hour, exterior humidity, exterior humidity change from the preceding hour, interior air temperature, interior air temperature change from the preceding 10 min, interior humidity and interior humidity change from the preceding 10 min and three neurons in output layer representing temperature change, humidity change and PMV. Their results reported that ANN based predictive and adaptive control strategies created more comfortable thermal conditions in the air conditioning buildings compared to conventional thermostat systems.

4.7.3. *Static and dynamic response of a HVAC heat exchanger*

Hu et al. [94] predicted the static and dynamic performance of a HVAC heat exchanger using ANN. They used two ANN models for predicting the static and dynamic response of a heat exchanger used in a mechanical ventilation system. In their work, five input parameters (such as inlet chilled water temperature, outlet temperature of chilled water temperature, inlet temperature of hot air, mass flow rate of chilled water and mass flow rate) were used in the input layer for predicting the heat transfer rate of a heat exchanger. The network with 5-10-1 configuration predicts the heat transfer rate with errors less than 4.87%. They also developed another ANN model with ten neurons in the input layer and two neurons in the output layer for predicting the dynamic performance of a heat exchanger. The network with 10-20-2 configuration predicts the chilled water outlet temperature and outlet air temperature at the with maximum relative error of 11.42% and 6.94%, respectively.

4.7.4. *Optimum start point of heating systems*

Yang et al. [95] developed an optimized ANN model to predict the optimum start time for a heating system in an air conditioning building with reference to room air temperature, varying rate of room air temperature, outdoor air temperature and varying rate of outdoor air temperature. They developed a MLFFN with four neurons in the input layer and one neuron in the output layer. The optimal values of the ANN parameters such as learning rate, momentum factor, number of hidden layers and number of neurons in the hidden layer are 0.75, 0.9, 1 and 8, respectively. The optimized ANN model determines the start time of the heating system accurately with coefficients of determination in the range of 0.968–0.996.

4.7.5. *Air conditioning cooling load forecasting*

Hou et al. [96] predicted the cooling load of an air conditioned room by a combination of rough set theory and an ANN based on data fusion technique (defined as the merging of information from different data sources). In their work, rough set theory was applied to identify the relevant factors to cooling load, which are used as inputs to ANN. Rough set theory provides techniques to reduce irrelevant and unnecessary attributes from a large database with a lot of attributes. Their results reported that multi rough set ANN forecasting model predicts the cooling load with an average relative error less than 4%, which is better than autoregressive integrated moving average (ARIMA). Yao et al. [97] developed RBFNN model with combined residual error correction to forecast the air-conditioning load for the optimal control and energy saving operation of HVAC systems. They developed four models such as multiple linear regression (MLR), ARIMA, grey model (GM) and ANN for predicting the air-conditioning load. None of these models has enough accuracy to satisfy the practical load demand. In their work, a novel forecasting method using RBFNN with combined residual error correction (which is the combination of MLR, ARIMA and GM, to estimate the residual errors and correct the ultimate foresting results) was developed for the air-conditioning load forecasting. The results using RBFNN combined with residual error correction was reported to more effective within 10% in most cases. The accuracy of four ANN modeling techniques for the prediction of hourly cooling load in an air conditioning building was compared [98]. In their work, the traditional MLFFN using BPA, the RBFNN, GRNN and support vector mechanism (SVM) were used for predicting the cooling load of an air conditioning building. Out of four models investigated, SVM and GRNN methods can achieve better accuracy and generalization than other two models such as MLFFN and RBFNN.

4.7.6. *Thickness of insulation of an air conditioning building*

The thickness of insulation of an air conditioning building was predicted by using MLFFN with reference to five parameters such as maximum overall heat transfer coefficient, lowest temperature in meteorological data, lowest temperature in TSE data, total wall thermal resistance and heat transfer rate in TSE [99]. The network with 5-7-1 configuration predicts the thickness of insulation with RMS, mean relative error value and R^2 values of 0.0001, 0.01 and 0.998, respectively.

Table 7
Applications of ANN for HVAC systems.

Authors [references]	Network architectures	Year	Applications
Moon and Kim [93]	MLFFN	2010	Predicted mean vote
Hu et al. [94]	MLFFN	2005	Static and dynamic response of heat exchanger
Yang et al. [95]	MLFFN	2003	Optimum start point of heating systems
Yao et al. [97]	RBFFN	2006	Air conditioning load forecasting
Tosun and Dincer [99]	MLFFN	2011	Thickness of insulation

Table 8
Applications of ANN for special purpose heating and cooling applications.

Authors [references]	Network architectures	Year	Applications
Wu et al. [100]	MLFFN	2008	CO_2 gas cooler
Kocabas et al. [101]	MLFFN	2010	Vortex tube cooling and heating
António and Afonso [103]	MLFFN	2011	Domestic refrigerator temperature prediction
Kiran and Rajput [104]	MLFFN	2011	Indirect evaporative cooling system

4.8. Special purpose cooling and heating applications

ANN has been successfully applied in special purpose cooling and heating applications with acceptable accuracy. In this subsection, review of few special purpose cooling and heating applications of ANN is discussed. A summary of ANN applications for special purpose heating and cooling applications are presented in Table 8.

4.8.1. Performance of a gas cooler in a carbondioxide heat pump

Wu et al. [100] used MLFFN for performance prediction of a gas cooler in a carbon dioxide (CO_2) heat pump. They developed a network with five neurons in input layer (representing temperature of CO_2 at the gas cooler inlet, pressure of CO_2 at the gas cooler inlet, mass flow rate of CO_2 through the gas cooler, temperature of air passing through the cooler and velocity of air) and four neurons in output layer (representing temperature of the CO_2 at the cooler outlet, pressure raise in the cooler, temperature of the air at the cooler outlet and heat transfer rate). The results generated using 5-5-4-4 network configuration predicts the performance with maximum deviations of 1.81%, 5.4%, 8.5% and 7.03% for temperature of CO_2 at the cooler outlet, pressure raise in the cooler, temperature of air at the cooler outlet and heat transfer rate, respectively.

4.8.2. Heating and cooling performance of the vortex tube

Kocabas et al. [101] developed a MLFFN model with four neurons in input layer (represents inlet pressure, mass flow rate, cold mass fraction and nozzle number) and one neuron in output layer (represents the temperature difference between hot and cold outlets) for predicting the cooling and heating performance of the vortex tube. It was reported that network using 4-7-1 configuration yields good statistical performance values with R^2, RMS error and relative absolute error of 0.9989, 0.5016 and 0.0540, respectively. In similar work, the effect of nozzle number, inlet pressure and cold mass fraction on heating and cooling performance (temperature gradient between the cold and hot outlets) of counter flow type vortex tube was predicted by using ANN [102]. The back-propagation learning algorithm with LM variant and Fermi transfer function were used in their network. It was reported that network predicts the temperature gradient between hot and cold junctions with R^2 value of 0.9947, root mean square error of 0.188224 and mean absolute error percentage of 0.0460.

4.8.3. Temperature prediction inside the refrigerators

The temperatures in a refrigerator were measured with thermocouples and compared with two simulation tools such as computational fluid dynamics (CFD) and ANN with genetic algorithm [103]. They developed MLFFN with five inputs (Cartesian coordinates of the refrigerator, one time instant for the transient phase and one time instant for the stationary phase of the refrigeration process), where as the outputs are the simulated air temperature fields corresponding to the transient and steady phases of process. Genetic algorithm was used to optimize the network structure. It was reported that absolute error between the experimentally measured and ANN predicted temperatures is 0.8 K, where as CFD predictions have absolute error of 1 K. Their study confirmed that ANN predictions of temperature inside the refrigerator were reported better compared to CFD predictions.

4.8.4. Performance of an indirect evaporative cooling system

Kiran and Rajput [104] predicted the performance of an indirect evaporative cooling system using three artificial intelligence techniques such as MLFFN, ANFIS and fuzzy interface systems (FIS). The inputs to network are primary and secondary mass flow rate of air, ambient dry bulb and wet bulb temperature, whereas the outputs are outlet temperature of air and effectiveness. It was reported that ANN model predicts the performance of an indirect evaporative cooling system with good accuracy compared to other techniques.

5. Limitations of ANN modeling

The limitations of ANN modeling are over training, extrapolation and network optimization. A review of limitations of ANN is presented in this subsection.

5.1. Over training of network

Over training occurs when the capacity of ANN for training is too high or too many training iterations were allowed [105]. In most of the engineering applications of ANN, a very high training precision of 10^{-6} or large number of training cycles is preset to terminate the training processes. Nevertheless, in actual engineering systems, few training samples are usually erroneous due to experimental uncertainties. Hence too high precision will over fit the training samples and degrade the prediction performance of ANN model. To overcome the problem of over training with ANN, the number of training cycles and number of training data need to be optimized.

5.2. Extrapolation

ANN models are not effective for extrapolation beyond the training data [105]. While preparing the training data, firstly, the maximum and minimum values of the parameters are selected from the experimental samples. Secondly, some artificial training samples can be drawn from the existing empirical formulae which cover the entire rage as much as possible. The range of the training data must be representative of entire operating range of the equipment as much as possible.

5.3. Network optimization

Selection of optimum network parameters such as number of neurons in hidden layer, number of hidden layer, momentum factor, learning rate, number of training data and variant are major task in ANN modeling. To overcome these limitations, Mohebbi et al. [63] introduced a genetic algorithm based ANN approach to optimize the network parameters. The optimum network parameters have been determined using genetic algorithm to minimize the time and effort. Genetic algorithm is found to be a good alternative over the conventional trial and error approach to optimize the network configuration quickly and efficiently.

6. Future research scope

Based on the extensive literature reviewed, it was observed that ANN can be successfully used for modeling and performance

prediction of RACHP systems. The further research extensions using ANN are possible in the following areas:

(i) Hybridization of ANN with other expert systems.
(ii) Forecasting of environmental impacts of RACHP systems.
(iii) Clean development mechanism (CDM) using ANN in RACHP sectors.
(iv) Design of condensers and evaporators using new refrigerant mixtures.
(v) A simplified approach for optimizing the network configuration.
(vi) Control of RACHP equipments using hybridized ANN.
(vii) Development of simplified correlation for predicting refrigerant properties.
(viii) Development of simplified correlations for predicting the performance of RACHP systems.
(ix) Phase change behavior of newly developed refrigerant mixtures.

7. Conclusion

More than ninety published papers with applications of ANN for modeling, performance forecasting, controlling of RACHP systems, cooling load forecasting and prediction of refrigerant properties were reviewed. The published literatures presented in this paper confirmed that ANN can be successfully used in RACHP applications with acceptable accuracy. MLFFN was widely used in RACHP applications. The hybridization of ANN with other expert systems showed better performance compared to conventional ANN approach. The limitations with ANN models and future research scope in RACHP field were also highlighted. Information presented in this paper may be useful to the researchers working in this area.

References

[1] Kalogirou SA. Artificial intelligence for the modeling and control of combustion processes: a review. Progress in Energy and Combustion Science 2003;29:515–66.
[2] Mellit A, Kalogirou SA. Artificial intelligence techniques for photovoltaic applications: a review. Progress in Energy and Combustion Science 2008;34:574–632.
[3] Tayagarajan T, Poonavaikko M, Shanmugam J, Panda RC, Rao PG. Artificial neural networks: Principles and application to model based control of drying systems – a review. Drying Technology 1998;16:931–66.
[4] Zhang G, Zhang BE, Patuwo M, Hu Y. Forecasting with artificial neural networks. The state of the art. International Journal of forecasting 1998;14:35–62.
[5] Gardner MW, Dorling SR. Artificial neural networks (the multilayer perceptron) – a review of applications in the atmospheric sciences. Atmospheric Environment 1998;32:2627–36.
[6] Mellit A, Kalogirou SA, Hontoria L, Shaari S. Artificial intelligence techniques for sizing photovoltaic systems: a review. Renewable and Sustainable Energy Reviews 2009;13:406–19.
[7] Kalogirou S. Applications of artificial neural networks in energy systems: a review. Energy Conversion and Management 1999;40:1073–87.
[8] Kalogirou SA. Applications of artificial neural networks for energy systems. Applied Energy 2000;67:17–35.
[9] Kalogirou SA. Artificial neural networks in renewable energy systems applications: a review. Renewable and Sustainable Energy Reviews 2001;5:373–401.
[10] Ding G-l. Recent developments in simulation techniques for vapour-compression refrigeration systems. International Journal of Refrigeration 2007;30:1119–33.
[11] Jang J-SR. ANFIS: adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man and Cybernetics 1993;23:665–85.
[12] Hosoz MH, Ertunc M. Modeling of a cascade refrigeration system using artificial neural networks. International Journal of Energy Research 2006;30:1200–15.
[13] Yilmaz S, Atik K. Modeling of a mechanical cooling system with variable cooling capacity by using artificial neural network. Applied Thermal Engineering 2007;27:2308–13.
[14] Ertunc HM, Hosoz M. Artificial neural network analysis of a refrigeration system with an evaporative condenser. Applied Thermal Engineering 2006;26:627–35.
[15] Saidur R, Masjuki HH, Jamiludhin MY. A new method to investigate the energy performance of a household refrigerator-freezer. International Energy Journal 2006;7:9–15.
[16] Swider DJ, Browne MW, Bansal PK, Kecman V. Modeling of vapour compression liquid chillers with neural networks. Applied Thermal Engineering 2001;21:311–29.
[17] Navarro-Esbrı J, Berbegallb V, Verdub G, Cabelloa R, Llopis R. A low data requirement model of a variable-speed vapour compression refrigeration system based on neural networks. International Journal of Refrigeration 2007;30:1452–9.
[18] Chang Y-C. Sequencing of chillers by estimating chiller power consumption using artificial neural networks. Building and Environment 2007;42:180–8.
[19] Hosoz M, Ertunc MH. Artificial neural network analysis of an automobile air conditioning system. Energy Conversion and Management 2006;47:574–87.
[20] Atik K, Aktas A, Deniz E. Performance parameters estimation of MAC by using artificial neural network. Expert Systems with Applications 2010;37:5436–42.
[21] Bacthler H, Browne MW, Bansal PK, Kecman V. Neural networks—A new approach to model vapour compression heat pumps. International Journal of Energy Research 2001;25:591–9.
[22] Arcaklioglu E, Erisen A, Yilmaz R. Artificial neural network analysis of heat pumps using refrigerant mixtures. Energy Conversion Management 2004;45:1917–29.
[23] Arcaklioglu E. Performance comparison of CFCs with their substitutes using artificial neural network. International Journal of Energy Research 2004;28:1113–25.
[24] Esen H, Inalli M, Sengur A, Esen M. Performance prediction of a ground-coupled heat pump system using artificial neural networks. Expert Systems with Applications 2008;35:1940–8.
[25] Esen H, Inalli M. Modelling of a vertical ground coupled heat pump system by using artificial neural networks. Expert Systems with Applications 2009;36:10229–1038.
[26] Esen H, Inalli M, Sengur A, Esen M. Forecasting of a ground-coupled heat pump performance using neural networks with statistical data weighting pre-processing. International Journal of Thermal Sciences 2008;47:431–41.
[27] Esen H, Inalli M, Sengur A, Esen M. Artificial neural networks and adaptive neuro-fuzzy assessments for ground-coupled heat pump system. Energy and Buildings 2008;40:1074–83.
[28] Mohanraj M, Jayaraj S, Muraleedharan C. Performance prediction of a direct expansion solar assisted heat pump using artificial neural networks. Applied Energy 2009;86:1441–9.
[29] Mohanraj M, Jayaraj S, Muraleedharan C. Exergy analysis of a direct expansion solar assisted heat pump using artificial neural networks. International Journal of Energy Research 2009;33:1005–20.
[30] Mohanraj M, Jayaraj S, Muraleedharan C. Exergy assessment of direct expansion solar assisted heat pump working with R22 and R407C/LPG mixture. International Journal of Green Energy 2010;7:65–83.
[31] Yang L, Zhao L-X, Zhang C-L, Gu B. Loss-efficiency model of single and variable-speed compressors using neural networks. International Journal of Refrigeration 2009;32:1423–32.
[32] Sanaye S, Dehghandokht M, Beigi MH, Bahrami S. Modeling of rotary vane compressor applying artificial neural network. International Journal of Refrigeration 2011;34:764–72.
[33] Islamoglu Y. A new approach for the prediction of the heat transfer rate of the wire-on-tube type heat exchanger—use of an artificial neural network model. Applied Thermal Engineering 2003;23:243–9.
[34] Hayati M, Rezaei A, Seifia M. Prediction of the heat transfer rate of a single layer wire-on-tube type heat exchanger using ANFIS. International Journal of Refrigeration 2009;32:1914–7.
[35] Ertunc HM, Hosoz M. Comparative analysis of an evaporative condenser using artificial neural network and adaptive neuro-fuzzy inference system. International Journal of Refrigeration 2008;31:1426–36.
[36] Zhao L-X, Zhang C-L. Fin-and-tube condenser performance evaluation using neural networks. International Journal of Refrigeration 2010;33:625–34.
[37] Pacheco-Vega A, Sen M, Yang KT, McClain RL. Neural network analysis of an-tube refrigerating heat exchanger with limited experimental data. International Journal of Heat and Mass Transfer 2001;44:763–70.
[38] Yigit KS, Ertunc HM. Prediction of the air temperature and humidity at the outlet of a cooling coil using neural networks. International Communications in Heat and Mass Transfer 2006;33:898–907.
[39] Islamoglu Y, Kurt A, Parmaksizoglu C. Performance prediction for non-adiabatic capillary tube suction line heat exchanger: an artificial neural network approach. Energy Conversion and Management 2005;46:223–32.
[40] Zhang C-L. Generalized correlation of refrigerant mass flow rate through adiabatic capillary tubes using artificial neural network. International Journal of Refrigeration 2005;28:506–14.
[41] Zhao L-X, Zhang C-L, Shao L-L, Yang L. A generalized neural network model of refrigerant mass flow through adiabatic capillary tubes and short tube orifices. ASME Journal of Fluids Engineering 2007;129:1559–64.
[42] Zhang C-L, Zhao L-X. Model-based neural network correlation for refrigerant mass flow rates through adiabatic capillary tubes. International Journal of Refrigeration 2007;30:690–8.
[43] Yang L, Zhang C-L. Modified neural network correlation of refrigerant mass flow rates through adiabatic capillary and short tubes: extension to CO_2 transcritical flow. International Journal of Refrigeration 2009;32:1293–301.

[44] Vinš V, Vacek V. Mass flow rate correlation for two-phase flow of R218 through a capillary tube. Applied Thermal Engineering 2009;29:2816–23.
[45] Hosoz M, Ertunc HM, Bulgurcu H. Performance prediction of a cooling tower using artificial neural network. Energy Conversion and Management 2007;48:1349–59.
[46] Gao M, Sun F-Z, Zhou S-J, Shi Y-T, Zhao Y-B, Wang N-H. Performance prediction of wet cooling tower using artificial neural network under cross-wind conditions. International Journal of Thermal Sciences 2009;48:583–9.
[47] Hosoz M, Ertun HM, Ozguc AF. Modelling of a direct evaporative air cooler using artificial neural network. International Journal of Energy Research 2008;32:83–9.
[48] Sun DW. Thermodynamic design data and optimum design maps for absorption refrigeration systems. Applied Thermal Engineering 1997;17:211–21.
[49] Sozen A, Arcaklioglu E, Ozalp M. A new approach to thermodynamic analysis of ejector-absorbtion cycle: artificial neural networks. Applied Thermal Engineering 2003;23:937–52.
[50] Sözen A, Arcaklioglu E, Ozalp M. Performance analysis of ejector absorption heat pump using ozone safe fluid couple through artificial neural networks. Energy Conversion and Management 2004;45:2233–53.
[51] Sozen A, Akcayol MA. Modelling (using artificial neural networks) the performance parameters of a solar-driven ejector-absorption cycle. Applied Energy 2004;79:309–25.
[52] Manohar HJ, Saravanan R, Renganarayanan S. Modelling of steam fired double effect vapour absorption chiller using neural network. Energy Conversion and Management 2006;47:2202–10.
[53] Şencan A. Artificial intelligent methods for thermodynamic evaluation of ammonia–water refrigeration systems. Energy Conversion and Management 2006;47:3319–32.
[54] Sencan A. Performance of ammonia–water refrigeration systems using artificial neural networks. Renewable Energy 2007;32:314–28.
[55] Rosiek S, Batlles FJ. Modelling a solar-assisted air-conditioning system installed in CIESOL building using an artificial neural network. Renewable Energy 2010;35:2894–901.
[56] Sozen A, Arcaklioglu E. Exergy analysis of an ejector-absorption heat transformer using artificial neural network approach. Applied Thermal Engineering 2007;27:481–91.
[57] Chow TT, Zhang GQ, Lin Z, Song CL. Global Optimization of absorption chiller system by genetic algorithm and neural network. Energy and Buildings 2002;34:103–9.
[58] Chouai A, Laugeier S, Richon D. Modelling of thermodynamic properties using neural networks—application to refrigerants. Fluid Phase Equilibria 2002;199:53–62.
[59] Sozen A, Ozalp M, Arcaklioglu E. Calculation for the thermodynamic properties of an alternative refrigerant (R508B) using artificial neural network. Applied Thermal Engineering 2007;27:551–9.
[60] Sozen A, Arcaklioglu E, Menlik T, Ozalp M. Determination of thermodynamic properties of an alternative refrigerant (R407C) using artificial neural network. Expert Systems with Applications 2009;36:4346–56.
[61] Sozen A, Arcaklioglu E, Menlik T. Derivation of empirical equations for thermodynamic properties of a ozone safe refrigerant (R404A) using artificial neural network. Expert Systems with Applications 2010;37:1158–68.
[62] Scalabrin G, Cristofoli G. The viscosity surfaces of R152a in the form of multilayer feed forward neural networks. International Journal of Refrigeration 2003;26:302–14.
[63] Mohebbi A, Taheri M, Soltani A. A neural network for predicting saturated liquid density using genetic algorithm for pure and mixed refrigerants. International Journal of Refrigeration 2008;31:1317–27.
[64] Sencan A, Kose II, Selbas R. Prediction of thermophysical properties of mixed refrigerants using artificial neural network. Energy Conversion and Management 2011;52:958–74.
[65] Moghadassi AR, Nikkholgh MR, Parvizian F, Hosseini SM. Estimation of thermophysical properties of dimethyl ether as a commercial refrigerant based on artificial neural networks. Expert Systems with Applications 2010;37:7755–61.
[66] Kurt H, Kayfeci M. Prediction of thermal conductivity of ethylene glycol–water solutions by using artificial neural networks. Applied Energy 2009;86:2244–8.
[67] Eslamloueyan R, Khademi MH. Estimation of thermal conductivity of pure gases by using artificial neural networks. International Journal of Thermal Sciences 2009;48:1094–101.
[68] Sozen A, Ozalp M, Arcaklioglu E. Investigation of thermodynamic properties of refrigerant/absorbent couples using artificial neural networks. Chemical Engineering and Processing 2004;43:1253–64.
[69] Sozen A, Arcaklioglu E, Ozalp M. Formulation based on artificial neural network of thermodynamic properties of ozone friendly refrigerant/absorbent couples. Applied Thermal Engineering 2005;25:1808–20.
[70] Sencan A, Yakut KA, Kalogirou SA. Thermodynamic analysis of absorption systems using artificial neural network. Renewable Energy 2006;31:29–43.
[71] Urata S, Takada A, Murata J, Hiaki T, Sekiya A. Prediction of vapor–liquid equilibrium for binary systems containing HFEs by using artificial neural network. Fluid Phase Equilibria 2002;199:63–78.
[72] Mohanty S. Estimation of vapour liquid equilibria for the system carbon dioxide–difluoromethane using artificial neural networks. International Journal of Refrigeration 2006;29:243–9.
[73] Tian J, Feng Q, Zhu R. Analysis and experimental study of MIMO control in refrigeration system. Energy Conversion and Management 2008;49:933–9.
[74] Palau A, Velo E, Puigjaner L. Use of neural networks and expert systems to control a gas/solid sorption chilling machine. International Journal of Refrigeration 1999;22:59–66.
[75] Nanayakkaraa VK, Ikegamib Y, Ueharab H. Evolutionary design of dynamic neural networks for evaporator control. International Journal of Refrigeration 2002;25:813–26.
[76] Abbassi A, Bahar L. Application of neural network for the modeling and control of evaporative condenser cooling load. Applied Thermal Engineering 2005;25:3176–86.
[77] Tse WL, Chan WL. An automatic data acquisition system for on-line training of artificial neural network-based air handling unit modeling. Measurement 2005;37:39–46.
[78] Ekren O, Sahin S, Isler Y. Comparison of different controllers for variable speed compressor and electronic expansion valve. International Journal of Refrigeration 2010;33:1161–8.
[79] Soyguder S. Intelligent system based on wavelet decomposition and neural network for predicting of fan speed for energy saving in HVAC system. Energy and Buildings 2011;43:814–22.
[80] Khayyam H, Kouzani AZ, Hu EJ, Nahavandi S. Coordinated energy management of vehicle air conditioning system. Applied Thermal Engineering 2011;31:750–64.
[81] Wu J-D, Liao S-Y. Fault diagnosis of an automotive air-conditioner blower using noise emission signal. Expert Systems with Applications 2010;37:1438–45.
[82] Wu J-D, Liao S-Y. A self-adaptive data analysis for fault diagnosis of an automotive air-conditioner blower. Expert Systems with Applications 2011;38:545–52.
[83] Rajapaksha L. Influence of special attributes of zeotropic refrigerant mixtures on design and operation of vapour compression refrigeration and heat pump systems. Energy conversion and Management 2007;48:539–45.
[84] Demir H, Ağra O, Atayılmaz O. Generalized neural network model of alternative refrigerant (R600a) inside a smooth tube. International Communications in Heat and Mass Transfer 2009;36:744–9.
[85] Balcilar M, Dalkilic AS, Wongwises S. Artificial neural network techniques for the determination of condensation heat transfer characteristics during downward annular flow of R134a inside a vertical smooth tube. International Communications in Heat and Mass Transfer 2011;38:75–84.
[86] Wang W-J, Zhao L-X, Zhang C-L. Generalized neural network correlation for flow boiling heat transfer of R22 and its alternative refrigerants inside horizontal smooth tubes. International Journal of Heat and Mass Transfer 2006;49:2458–65.
[87] Scalabri G, Condosta M, Marchi P. Modeling flow boiling heat transfer of pure fluids through artificial neural networks. International Journal of Thermal Sciences 2006;45:643–63.
[88] Scalabrin G, Condosta M, Marchi P. Mixtures flow boiling: modeling heat transfer through artificial neural networks. International Journal of Thermal Sciences 2006;45:664–80.
[89] Kalogirou SA, Bojic M. Artificial neural networks for the prediction of the energy consumption of a passive solar building. Energy 2000;25:479–91.
[90] Aydinalp M, Ugursal VI, Fung AS. Modeling of the appliance, lighting, and space cooling energy consumptions in the residential sector using neural networks. Applied Energy 2002;71:87–110.
[91] Yang KH, Su CH. An approach to building energy savings using the PMV index. Building Environment 1997;32:25–30.
[92] Atthajariyakul S, Leephakpreeda T. Neural computing thermal comfort index for HVAC systems. Energy Conversion and Management 2005;46:2553–65.
[93] Moon JW, Kim J-J. ANN-based thermal control models for residential buildings. Building and Environment 2010;45:1612–25.
[94] Hu Q, So ATP, Tse WL, Ren Q. Development of ANN based models to predict the static and dynamic response of a heat exchanger in a real MVAC system. Journal of Physics: Conference Series 2005;23:110–21.
[95] Yang I-H, Yeo M-S, Kim K-W. Application of artificial neural network to predict the optimal start time for heating system in building. Energy Conversion and Management 2003;44:2791–809.
[96] Hou Z, Lian Z, Yao Y, Yuan X. Cooling-load prediction by the combination of rough set theory and an artificial neural-network based on data-fusion technique. Applied Energy 2006;83:1033–46.
[97] Yao Y, Lian Z, Hou Z, Liu W. An innovative air conditioning load forecasting model based on RBF neural network and combined residual error correction. International Journal of Refrigeration 2006;29:528–38.
[98] Li Q, Meng Q, Cai J, Yoshino H, Mochida A. Predicting hourly cooling load in the building: a comparison of support vector machine and different artificial neural networks. Energy Conversion and Management 2009;50:90–6.
[99] Tosun M, Dincer K. Modelling of a thermal insulation system based on the coldest temperature conditions by using artificial neural networks to determine performance of building for wall types in Turkey. International Journal of Refrigeration 2011;34:362–73.
[100] Wu ZG, Zhang JZ, Tao YB, He YL, Tao WQ. Application of artificial neural network method for performance prediction of a gas cooler in a CO_2 heat pump. International Journal of Heat and Mass Transfer 2008;51:5459–64.
[101] Kocabas F, Korkmaz M, Sorgucu U, Donmez S. Modeling of heating and cooling performance of counter flow type vortex tube by using artificial neural network. International Journal of Refrigeration 2010;33:963–72.
[102] Uluer O, Kirmaci V, Atas S. Using the artificial neural network model for modeling the performance of the counter flow vortex tube. Expert Systems with Applications 2009;36:12256–63.

[103] António CC, Afonso CF. Air temperature fields inside refrigeration cabins: a comparison of results from CFD and ANN modeling. Applied Thermal Engineering 2011;31:1244–51.
[104] Kiran RT, Rajput SPS. An effectiveness model for an indirect evaporative cooling (IEC) system: comparison of artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) and fuzzy inference system (FIS) approach. Applied Soft Computing 2011;11:3525–33.
[105] Yin C, Rosendahl L, Luo Z. Methods to improve prediction performance of ANN models. Simulation Modelling Practice and Theory 2003;11:211–22.